Comparative study of similarity measures for item based top n recommendation

A thesis submitted in partial requirements for the degree of

Bachelor of Technology in Computer Science and Engineering

By

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Certificate

This is to certify that this report, entitled "Comparative study of similarity measure for item based top n recommendation ", submitted by Madhuri Angel Baxla in partial fulfilment for the requirements for the award of Bachelor of Technology Degree in Computer Science and Engineering at National Institute of Technology, Rourkela (Deemed University) is an authentic work carried out by her under my supervision and guidance.

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Abstract

The objective of the present work is to evaluate and analyse the total execution time of the generation of Top-N recommendation list by using the item based collaborative filtering(CF) approach. Different similarity measures are the key for the analysis. The user based collaborative filtering approach has some flaws, so item based collaborative filtering approach is taken into consideration. Different similarity measure like cosine based similarity, adjusted cosine similarity, extended jaccard co-efficient and correlation based similarity has been used to compare the total execution time of the item based collaborative filtering approaches. Behaviour of both the item based CF approach is analysed taking different similarities measures into consideration.

For generation of Top N recommendation, dataset has been taken from the jester online joke recommender system. These datasets contains many users and about hundreds of jokes. This approach will predict the jokes (Prediction Problem (PP)) that the user is most likely that he/she may like. For prediction of jokes for the user the recommender system will look into the jokes that the users have previously rated or liked. By this recommendation it will be easier for user to choose the jokes which they may prefer to read. Recommender system (RS) is a personalized information filtering technology.

Different similarity measure has been used so as to see how the algorithm behaves with differently. Main aim to find out the advantages and disadvantages of the algorithm and which approach takes the least time to generate the Top-N recommendation list using which similarity measure.

Keywords: CF, PP, RS

Chapter 1

1.1 Introduction

Recommender system is an system which filters the information for recommending some items to its users, it filters the data and recommends the items. It is commonly used in movie lens, book-crossing, jester , wiki-lens that uses a collaborative filtering to present information on items and products that are likely to be of interest to the reader/consumers. User's interest in the past is seen and analysed for the recommendation of any items. While presenting the recommendations, the recommender system uses details of the account of the registered user's profile , behaviour, preferences and habit of their whole group of users and comparison of the information to present the recommendations.

1.1.1 Types of recommender system

- **Content-based**: This system processes to recommend items that are almost alike to the ones that the user wished or desired in the past. It gives preferences to the features of the products, movie , jokes, book etc. Similarity is checked for the items which the user had likes previously. The similarity of items is calculated based on the features associated with the compared items. It has to recommend some item to the users, and there is the job to produce a list of items to be recommended, the most similar users are needed to be found out or items are found after evaluating the commonalities, and then consider the neighbours to get the top most common items as the list of items recommended.

- **Collaborative filtering:** Collaborative filtering is a method of identifying the similar clients and recommending what the common clients prefer. This system recommends items to the active user or the target users with that of the other users with similar preferences in the past. The similarity in preferences of the two users is calculated/ evaluated based on the similarity in the rating history of the different users. This is the reason why it's also known as "people-to-people correlation." This filtering is considered to be the most popular and widely implemented technique in Recommender Systems. There are several methods that implements collaborative

filtering. Neighbourhood methods gives stress on relationships between items or, alternatively, between users.

The item-item approach models the preferences of a user to an item based on ratings of similar items by the same user. Nearest-neighbours methods are more popular than the item-item approach models. Nearest-neighbours methods are mostly used due to the considerable popularity due to their simplicity, efficiency, and their ability to produce accurate result and personalized recommendations for relatively smaller datasets. Several collaborative filtering algorithms have been composed essentially for information sets where there are a lot of people a larger number of customers than items (e.g., the jester online recommender data set has 73,421 users and 100 jokes).

- **Hybrid recommender systems**: It is the combination of content and collaborative filtering system. This recommender system is based on the combination of the content based system and the collaborative filtering system techniques. A hybrid system is a combining techniques where given X and Y, it tries to use the advantages of X to fix the disadvantages of Y.

  For example, Collaborative filtering system suffer from the new-item problems, i.e., they cannot recommend items that has not been rated by the users. Where as in case of the content based approach this problem doesn't limit its prediction for new items as content based is dependent on the features and description that are typically easily available.

1.2 Overview

A particular recommender system introduces a collection of recommender job which categorizes the client aim. The proper and accurate datasets are chosen or selected for the purpose of evaluation. The calculation on the datasets can also be successfully done off-line by the use of the old available datasets and may be sometimes it also requires the on-line trial.

The properties of the datasets is always considered and reviewed while selection of the datasets for the computation purpose. A survey is been done on the similarity metrics which will be used for the computation of the recommender system. Using those metrics we can also analyse the recommender system and its properties like its negative point and its positive points.

A report is been made on the obtained result and a comparison is been made by considering the different similarity metrics on the given datasets. By assessing a wide set of measurements on a dataset, we demonstrate that for a few datasets, while numerous distinctive measurements are emphatically connected, there are classes of measurements that are uncorrelated. We audit an extensive variety of non-exactness measurements, including measures of the degree to which proposals blanket the set of things, the variety and serendipity of suggestions, and client fulfillment and conduct in the recommender systems. To legitimately assess a recommender framework, it is vital to comprehend the objectives and errands for which it is, no doubt utilized. In this article, we concentrate on end-client objectives and undertakings (instead of objectives of advertisers and other framework stakeholders). We determine these undertakings from the exploration writing and from sent system. For each one undertaking, we talk about its suggestions for assessment. While the errands we've recognized are vital ones, in light of our experience in recommender frameworks research and from our survey of distributed examination, we perceive that the schedule is fundamentally deficient.

1.1.2 Filtering algorithm for collaborative approach

User based Collaborative filtering algorithmic approach

This methodology is known for its straightforwardness and its productivity. Client-based Collaborative sifting algorithm produces suggestion of items for target client as per the perspective purpose of different clients. The suppositions which is made here is that if the appraisals of a few things are evaluated by some other clients are comparative, then the rating of different things appraised by these same clients will likewise be comparable or indistinguishable . Collective Filtering proposal framework utilizes the factual strategies to pursuit the closest neighbours of the target client and afterward contemplating on the thing rating evaluated by the closest neighbours to do the expectation of the thing rating appraised by the target client, and after that generate relating top N suggestion of the items.

Collaborative Filtering framework that uses an area based algorithm is as takes after.
In neighbourhood based algorithms, first step is that a subset of clients are picked focused around their closeness to the dynamic client, and a weighted combo of their appraisals is utilized to generate expectations of items for the dynamic client.

Item based Collaborative filtering algorithmic approach

In this item based approach, we mainly look into that how a particular item is liked or rated by the users. According to the ratings given by the users to the items, the items are recommended to the users. Rating of the items are given preferences so as to recommend the products to its users. In contrary to the user-based collaborative filtering algorithm , the item-based algorithm looks into and analyses the collection of the items the desired user has already liked in the past and computes how much and to what extend they are similar to the target item *p* using some similarity measures and then select *k* most similar items *{p1,p2,p3…… ,pk}*. Side by side their respective similarities ,commonality *{si1,si2,si3…….,sik}* are also computed. Both calculation is done simultaneously.

After this once the most alike items are found, next step is the prediction of those most alike items , which is then computed by getting a different formula's of norm of the target user's ratings or target items ratings on those similar items. There are two main processes here the calculation of similarity between the items and then the prediction of the items to the desired user's.

The additional phase in the item-based CF algorithm is to evaluate the alikeness among items and then to selection of the most common items from them. The heart of the idea here lies is in the similarity evaluation between two item *p* and *q* , we separate the users who have co-rated both of these items and afte doing so we then to put forward a similarity measure computation method to determine the commonality between different items.

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1.3 Problem statement

The main problem is to calculate the similarity between the different items in the given dataset. For calculating the similarity between different items extended jaccard coefficient, cosine similarity, correlation based similarity, adjusted cosine similarity is used which predicts the result that is top-N recommendation list. So we have to discover out which of the similarity measure gives output(that is the recommendation of the items) in least time and efficiently. And what are the advantages and disadvantages of different similarity measure.

1.4 Motivation

The data that we are given from different online sites like jester online, amazon.in contains large amount of data user-item matrix. So any user who is using the facility of recommender system must be recommended with the top-N list of items as quick as possible so that the user will be recommended with items and he/she can browse it and can view it. With the increase in the online shopping sites or online joke sites, the number of users are also increasing and within less time good result is demanded by the users which they will also prefer. Hence, it is very important that recommendation list in generated in less time .

Recommender systems have several trends and its application of the information mining techniques to the problem of how to deliver the personalized recommendations to the users for information, products or items during a live interaction. High requirement of information and data mining is required here. All we need is to analyse over the data or the information in the database of the systems. The k-nearest neighbour is quite popular on the web. The rapid and everyday growth in the volume of available information and data, the count of clients to web sites in recent years poses some vital and tricky hurdles for recommender systems.

These are :

- How to produce recommendations that are of good quality for the users which satisfies them,
- How to recommend items to the users in the minimal time as possible,
- predicting several recommendations per second for millions of users,
- how to achieve high coverage when there is also data sparsity,
- Fast analysis over the users-item rating matrix whose dimensions are large.

In traditional as well as we can say today's collaborative filtering systems the amount of work to be done increases with the increase in the number of users in the system. Work done by the recommender system is directly proportional to the number of users increasing day in and day out.

Hence it has become very much necessary that the recommender system should be such that in case of high demand it can very accurately and quickly give predictions of the high quality recommendation lists even if the dataset is really large enough. And to cope up with the above problem we approach for the item-based top n recommendation algorithm. Item-based techniques dissects over the client-item matrix to recognize connections between distinctive items, and after that further utilize these connections to in a round about way to compute and recommends or forecasts of items for the clients. And obviously the recommended items to the users should be such that the users may like it.

1.5 Organisation of Thesis

The following chapters gives the outline and organization of the thesis with an emphasis on the contribution made.

Chapter 1: Introduction In this chapter we are going to discuss brief introduction and fundamental concepts about recommender system and collaborative filtering (CF) specifically item based collaborative filtering. It also gives idea why we are using different similarity measure and also gives some information about the similarity metrics. Evolution of recommender system from the generation of past till the present scenario. Challenges to be overcome by the recommender system as the number of users are increasing rapidly.

Chapter 2: Literature Review In this chapter we are going to discuss various journal, papers from where we collected the required information for the project. Analyse all the papers and cumulated all the data. What are the works done in the field of recommender system and what still is needed to be done is clearly known after reading these papers.

Chapter 3: Similarity Metrics In this chapter, we are going to discuss about different properties required for a similarity metrics. Correlation based similarity in detail and how user based collaborative filtering failed. There are number of similarity measure but some of them are used which are efficient enough to use with the data sets. For example for the datasets other than the binary attributes we cannot use the jaccard co-efficient because it is only for the evaluation of the jaccard co-efficient. Therefore appropriate similarity metrics are used for the study.

Chapter 4: Proposed Work

The item based collaborative filtering algorithmic approach is taken for the top N recommendation generation. This item based approach does the prediction of items to any particular active user by analysing over his past ratings. Therefore the ratings of each items are used for measuring the similarity between the items.

Different similarity measure has its own advantages and disadvantages, keeping this in mind we have used the similarity measures for comparison for prediction of items for the users.

Chapter 5: Result and Analysis

In this chapter the result are analysed based the output of the program. Large datasets is taken, computed the ratings of the items of different users and the result is taken out and is analysed. We get some result over which we do analysis.

Chapter 6: Conclusion

The conclusion which we draw from the project at last after completion.

Chapter 7: Scope for Future Work

In this chapter we discuss what is the future scope of improvement of the algorithm. How it will be used for betterment.

Chapter 8: Bibliography

In this chapter see over all the references from where we got vital information for doing the project.

Chapter 2

Literature review

Resnick et. al [1] brought into the original approach that is the user based approach. He determined the recommendations for the active user, identify similar users and compute a weighted average of their ratings of items not yet seen by the active user. Similarity is computed based on the users' historical rating behaviours.

Breese et. al [2] came up with an idea of prediction problem for collaborative filtering. He did empirical analysis of prediction algorithm. This prediction algorithm tries to guess the rating that a user is going to provide for an item. This user will be referred as active user and the item as an active item. These algorithms take advantage of the logged history of ratings and of content associated with users and items in order to provide predictions.

Herlocker et. al [3 audits distinctive key choices in assessing collaborative filtering recommender systems: the client assignments being assessed, the sorts of dissection and datasets being utilized, the courses in which expectation quality is measured, the assessment of forecast properties other than quality, and the client based assessment of the system all in all. Not with standing surveying the assessment techniques utilized by former specialists, experimental outcomes from the dissection of different precision measurements on one substance space where all the tried measurements broken down harshly into three proportionality classes were additionally inspected. Measurements inside every equivalency class were firmly related, while measurements from distinctive equivalency classes were uncorrelated.

Deshpande et. al [4] gave some contribution over the model-based recommendation approach that initially evaluates the commonalities between the several items. After that it uses the commonality to list the collection of items to be recommended to the active users.

He explained two important steps that are

(i) First how to use and which method to use for calculation of the similarity between the items.

(ii) The next step is the way applied to combine those similarities so as to compute the commonality between the items, the user already has purchased and is in his bag and a candidate recommender item.

Sarwar [6] analysed different item-based recommendation generation algorithms. He also dis survey on the several ways so for computing item-item similarities and also discussed different techniques for obtaining the high quality predictions from them. And finally evaluation of the result and analyse them with the basic k-nearest neighbour approach. It gives us a conclusion that if we take the item based algorithm in consideration it will provide much better execution time, quality than the user based CF algorithm. But the better quality is provided by the user based one .

Maddali Surendra Prasad Babu [7] expressed that collaborative filtering algorithms (CFAs) are the most prominent recommender system for teaming up each other to filter the records they read from the previous decade. CFA s have a few offers that make them not the same as different algorithms. The arrangement correctness is one among them. A client based collaborative oriented algorithms is one of the separating algorithms, known for their effortlessness and productivity. A study is led for its execution and its\ productivity as far as forecast unpredictability

Chapter 3

3.1 Similarity Metrics

Similarity are important because these are used by the number of data mining techniques for determining the similarity between the items or objects for different purposes as per requirement such as

- Clustering
- Anomaly detection
- Automatic categorization
- Correlation Analysis
- Nearest neighbour classification, search, and prediction
- Discrimination and characterization

Definition 3.1.1

Similarity: It is the numerical measure of the degree of which two items are alike. Items which are more alike have higher similarity between them. Similarity are often non-negative numbers and are fall generally in the range of [0,1], 0 for no similarity and 1 implies complete similarity.

Example of similarity measure are:

- Jaccard coefficient
- Cosine similarity
- Adjusted cosine similarity
- Dice coefficient etc.
- Correlation based similarity

- Extended Jaccard coefficient
- Mean squared difference

Definition 3.1.2

Dissimilarity: It is also the numerical measure of the degree to which the objects are different. For more similar objects the dissimilarity are lower value. Dissimilarity fall in the range of [0,1], with the upper range varying may be from zero to infinity.

Example of Dissimilarity metrics:

- Euclidean distance
- Minkowski distance
- Manhattan distance
- Hamming distance
- Jaccard Co-efficient similarity

Common properties of similarity metrics

Similarities have some well-known properties:

1. $s(x, y) = 1$ (or maximum similarity) only if $x = y$,
2. $s(x, y) = s(y, x)$ for all x and y, where $s(x, y)$ is the similarity between data objects, x and y.

3.2 Similarity Measure Used for the study

Cosine based Similarity

Moving forward to this similarity measure, any two things are taken as two items in the *s* dimensional client-space. The concept of angle is used here to calculate the similarity among the different items. The similarity between the two items is calculated by finding out the cosine of the angle between the taken any two items. Formally, in the $n \times m$ ratings matrix (that is user-item matrix) ,similarity between any items let suppose that we are taking the arbitrarily items *i* and *j*, denoted by

$$sim(i,j) = \cos(i,j) = \frac{i.j}{\|i\|\hat{}2 * \|j\|\hat{}2}$$

Advantage of Cosine-based similarity

- It is simple
- It is very efficient to evaluate
- Gives the value in between [0,1]

Disadvantage of cosine based similarity

- The variation in the ratings given to the items between the different users are not taken for the computation.

Correlation-based similarity

For this comparability measure, commonality between any two items let assume i and j is acquired by registering the given association based on likeness . Keeping in mind the end goal to make the association based calculation effective and doable we should from the beginning confine the co-evaluated conditions (i.e., situations where the clients have offered rating to both the thing i and j). Give us a chance to take that the set of clients who both appraised i and j are indicated by U then the correspondence similarity is given by

$$sim(i,j)= \frac{\sum u\in U\ (R(u,i)-*R(i))(R(u,j)-*R(j)}{\sqrt{\sum u\varepsilon U\big(R(u,i)-*R(i)\big)\text{^}2}\sqrt{\sum u\varepsilon U\big(R(u,j)-*R(j)\big)\text{^}2}}$$

Advantage of Correlation based similarity

- The computation is accurate.
- It does not calculate for the users, we isolate the condition where customers have rated both the item *i* and *j*.

Adjusted cosine similarity

The adjusted cosine similarity overcomes the drawback of the cosine based similarity. The main variation between the alikeness evaluation in client-based Collaborative filtering and item-based Collaborative filtering is that in a condition where the client-based CF the similarity is to be calculated taking considering the rows of the matrix where as in case of the item-based CF the commonality is evaluated taking along the columns. While the computation of the similarity using the ground level cosine measure in item-based consideration it has one vital flaw that is the differences in rating given by the users between different clients are not taken into view. The adjusted cosine similarity overcomes the above weaknesses by eliminating the corresponding user average or item rating norm from every co-rated items. By using the formula, the similarity between items *i* and *j* using the adjusted cosine similarity is given by

$$sim(i,j)= \frac{\sum u\in U\ (R(u,i)-*R(u))(R(u,j)-*R(u)}{\sqrt{\sum u\varepsilon U\big(R(u,i)-*R(u)\big)\text{^}2}\sqrt{\sum u\varepsilon U\big(R(u,j)-*R(u)\big)\text{^}2}}$$

Advantage of Adjusted cosine similarity

- Overcomes the drawback of cosine based similarity
- It subtracts the user average from each co-rated pair

Extended Jaccard Coefficient

This extended jaccard co-efficient can be used for the document data and this similarity measure gets reduced to Jaccard coefficient in case of the binary attributes. The extended Jaccard coefficient is also known as the Tanimoto coefficient. This co-efficient, which is represented as EJ, is defined by the following equation:

$$EJ(x,y)= x.y/ \|x\|\text{^}2 + \|y\|\text{^}2\text{-}x.y$$

Chapter 4

4.1 Proposed Work

Difficulty of the User-based Collaborative Filtering Algorithms

These filtering systems are in trend and are in popularity and also has been very flourishing in past, but their more use has brought into some troubling flaws such as:

Sparsity: Recommender system works over the large datasets comprising of the set of users and the items. So, in reality several recommender systems are extensively used to calculate over the given large data sets (for example, Amazon.com recommends books, jester.com recommends jokes and recommender music albums). If we consider the case that the users have purchased the items in a very less percentage from a large percentage of items, then as a result the concept of the on nearest neighbour algorithms seems to be incapable to predict any of the items for any of the target users. Aftermath is that the accuracy of recommendations will be poor.

Scalability: Day in and day out, the data and its users are increasing leading to the increase in the scalability of the datasets. Therefore the nearest neighbour algorithms is in utmost need so as quick evaluation that promotes both with the increase in count of users and the count of items. With long range of number of users and items, a well known recent recommender system running with the algorithms which is in existence, undergoes severe scalability problems. Nearest –nearest neighbour algorithm for large, differential databases is weak which leads to explore any alternative recommender system algorithms. So to handle the problem of scalability the item based collaborative approach is used for improvement.

4.2 Proposed Improvement

We take the item based approach for the improvement of challenges. The sole agenda here is to analyse the user-item given matrix so as to identify existing alikeness and relations among different products and then to use those similarity to derive the prediction of items for a given user for any particular item. The thought for taking the item based approach is that a customer will be more inclined to purchase those items that are alike in the features to the items the user had liked in the past and there will be high probability that he might obviously try to neglect items that are alike to the items the user who have not liked those in the past. In this technique there is no need to identify the neighbourhood of alike users when a prediction is to be made for the users, therefore as a output they will produce much faster items recommendations.

Chapter 5

5.1 Result

Similarity measure Taken

The cosine based similarity, extended jaccard based similarity, adjusted cosine based similarity and the correlation based similarity is taken for the comparison between different similarity metrics for item based top n recommendations.

The above similarity measures are taken and used in the item based top n recommendation algorithm. For the generation of recommendation list it has two phase.

Steps for generation of recommendation list using different similarity measures are as follows:

Phase 1

Input: User-item matrix n*m that is R and k that indicates the count of product to product similarities that will be stored for each product.

Result: m*m matrix M

Step 1: The user-item matrix is taken and item to item similarity is calculated using the different similarity measure that we have considered in the above for all the items that are not similar.

Step 2: The value of M(i,j) is compared with the k most similar items. If its same then it is left as the value is else it is made zero.

This is what we get the output matrix M, which will be used in the next phase of the algorithm.

Phase 2

Input: The output matrix M from the previous phase, the matrix m*1 U which store the products that has been purchased beforehand by the users, and the variable N that specifies the number of items that will be recommended to the users.

Output: m*1 matrix x that stores number of items to be recommended. Its non-zero value indicates that the items that is in top n and is recommended to its users.

Steps Involved in phase 2

Step 1: The matrix M and U are multiplied to get the result in x.

Step 2: Purchased items are found out and if the item is purchased then just the value is put as zero in matrix x.

Step 3: If any value in x in not equal to the n largest value among the matrix x, then its simply made as zero.

Step 4: The resultant value which we get at last in the matrix x that is the non-zero value is the top N items are recommended.

The two phases of the algorithm is implemented and run repeatedly using different similarity measures. While running the program the execution time of the whole program is being calculated to track which similarity measure is taking how much time to recommend items to the user's such that he may like it.

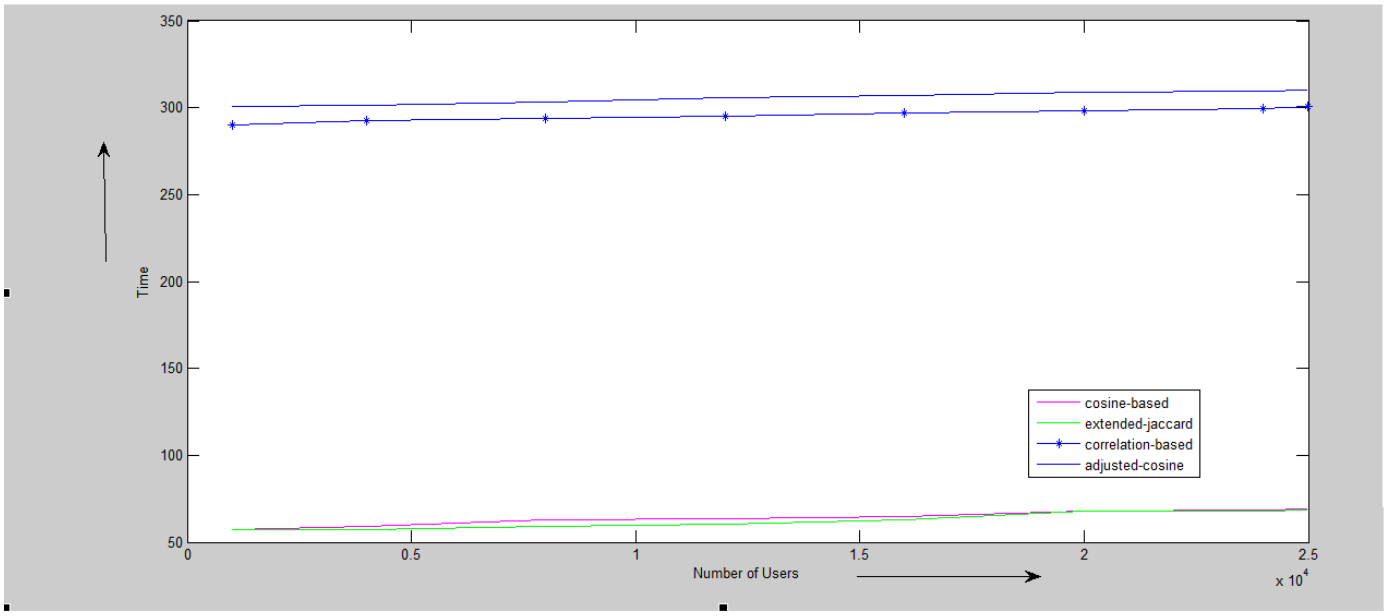
Table for execution time for different similarity measure

Number of Users	Cosine based similarity(sec)	Extended Jaccard based similarity(sec)	Adjusted cosine based similarity(sec)	Correlation based similarity(sec)
1000	56.9473	57.089	290.110	300.733
4000	59.138	57.373	292.613	301.065
8000	62.916	59.069	293.769	303.166
12000	63.412	60.156	295.112	305.794
16000	64.533	62.826	296.996	306.835
20000	68.090	67.612	298.119	308.617
24000	68.209	67.882	299.357	309.234
24893	69.127	68.215	301.021	310.109

5.2 Analysis

The item based top n recommendation algorithm is run again and again. We obtain some result which is on the above table and all the similarity measures having their execution time. Using those execution time all the similarity are compared with each other. To compare a graph is plotted to compare the performance of different similarity. How they differ from each other.

Graph showing comparison



And it is observed that the cosine and the extended jaccard similarity takes less execution time as compared to the adjusted based similarity and correlation based similarity. Among these four the extended jaccard takes the least time for execution.

Chapter 6

Conclusion

Similarity metrics are used to calculate how much similar all the items are to each other in the matrix. We implemented the algorithm and get the result accordingly. Comparison is made between them by plotting the graph which depicts which similarity measure takes how much time.

Hence, from the above table and graph it is concluded that the cosine based similarity and the extended jaccard similarity takes less time to recommend items to the active user in comparison to the adjusted cosine based similarity and the correlation based similarity.

Final conclusion is that among the taken four similarity measures the extended jaccard takes the least time to recommend items. At initial stage it is observed that when the users are less cosine similarity behaves better but as the number of users goes on increasing the extended jaccard similarity behaves much better than the all other taken similarity measures.

Chapter 7

Scope of future work

In this field there are several scope of doing future work such as:

- By using different similarity measure we can see which gives the most accurate answer when compared with the other similarity measures.
- If we take into consideration the recommendation of the recommender system in contrast with the real life preferences we can compare their mean absolute error.
- For collaborative filtering work can be done for serendipity and novelty.

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